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Paper Title and Affiliations:

"An Efficient Iris Segmentation Technique based on a Multiscale Approach"

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An Efficient Iris Segmentation Technique based on a Multiscale Approach

ABSTRACT
The use of biometric signatures, instead of tokens such as identification cards or computer passwords, continues to gain increasing attention as an efficient means of identification and verification of individuals for controlling access to secured areas, materials, or systems and a wide variety of biometrics has been considered over the years in support of these challenges. Iris recognition is especially attractive due to the stability of the iris texture patterns with age and health conditions. Iris image segmentation and localisation is a key step in iris recognition and plays an essential role the accuracy of matching. In this paper, we propose a new iris segmentation technique using a multiscale approach for edge detection, which is a fundamental issue in image analysis. Due to the presence of speckles, which can be modelled as a a strong multiplicative noise, edge detection for iris segmentation is very important and methods developed so far are generally applied in one single scale. In our proposed method, we introduce the concept of multiscale edge detection to improve iris segmentation. The technique is effecient for edge detetcion, greatly reduces the search space for the Hough transform and at the same time is robust to noise thus improving the overall performance. Linear Hough transform has been used for eyelids isolation, and an adaptive thresholding has been used for isolating eyelashes. Once the iris is segmented, a normalization step has been carried out by converting an iris image from cartesien into polar coordinates which are more suitable to deal with rotation and translation problems. Extensive experiments have been carried out and results obtained have shown an effectiveness of the proposed method which provides a high segmentation success of 99.6%.

Keywords
Biometrics, iris personnel identification, iris segmentation, multiscale edge detection, wavelet maxima, Hough transform.

1. INTRODUCTION
Consistent and protected identification of a person is a key subject in security. ID cards passwords and PINS are used for personal identification. In government and conventional environments, security is provided through badges, provision of information for visitors and issuing of keys. These are the most common means of identification since they are the easiest to remember and the easiest to confirm. However these means are the most unreliable putting all components of security at risk. IDs can be stolen; passwords can be forgotten or cracked. Security breaches resulting access to restricted areas of airports or power plans have caused terrorism. Although there are laws against false identification incidents of invasions and unauthorized modifications to information occur daily with catastrophic effects. Credit card fraud is rapidly increasing causing economic failure. Traditional technologies are not sufficient to reduce the impact of counterfeiting. Additional convenient security barriers are needed as our society gets *more* and more computer dependent. By keeping these points in mind it is needed to have a more secure technology to cope with the drawbacks and pitfalls of this traditional technology, so for this solution biometrics, the use of biology that deals with data statistically, provides an answer to this need since the uniqueness of *an* individual arises from his personal or behavioural characteristics with no passwords or numbers to remember. These include fingerprint, retinal and iris scanning, hand geometry, voice patterns, facial recognition and other techniques. The systems record data from the user and compare it each time the user is claimed.

Biometrics allows the provision of widely pertinent approaches to personal verification and identification. In the ‘verification’ mode, the user claims an identity and the system compares the extracted features with the stored template of the asserted identity to determine if the claim is true or false. In the ‘identification’ mode, no identity is claimed and the extracted feature set is compared with the templates of all the users in the database in order to recognize the individual. For such approaches to be widely applicable, they must be highly reliableeeje. Reliability related to the ability of the approach to support a signature that is unique to an individual and that can be captured in an invariant manner over time. The use of biometric indicia for identification purposes requires that a particular biometric factor be unique for each individual that it can be readily measured, and that it is invariant over time. Biometrics such as signatures, photographs, fingerprints, voiceprints and retinal blood vessel patterns all have significant drawbacks. Although signatures and photographs are cheap and easy to obtain and store, they are impossible to identify automatically with assurance, and are easily forged. Electronically recorded voiceprints are susceptible to changes in a person’s voice, and they can be counterfeited. Fingerprints or handprints require physical contact, and they also can be counterfeited and marred by artifacts.

Biometrics have the potential for high reliability because it is based on the measurement of an intrinsic physical property of an individual. Fingerprints, for example, provide signatures that appear to be unique to an individual an reasonably invariant with the passage of time, whereas faces, while fairly unique in appearance can vary significantly with time and place. Invasiveness has to do with the ability to capture the signature while placing as few constraints as possible on the subject of evaluation. In this regard, acquisition of a fingerprint signature is invasive as it requires that the subject makes physical contact with a sensor, whereas images of a subject's face or iris that are sufficient for recognition can required at a comfortable distance. Considerations of reliability and invasiveness suggest that the human iris is a particularly interesting structure on which to base a biometric approach for personnel verification and identification. From the point of view of reliability, the special patterns that are visually apparent in the human iris are highly distinctive to an individual, the appearance of any one iris suffers little from day to day variation. In addition, the method is nin-invasive since the iris is an overt body that can be imaged at a comfortable distance from a subject with the use of extant machine vision technology. Owing to these features of reliability and non invasiveness, iris recognition is a promising approach to biometric based verification and identification of people [1].

The authentication system based on iris recognition is reputed to be the most accurate among all biometrics methods because of its acceptance, reliability and accuracy. Ophthalmologists originally proposed that the iris of the eye might be used as a kind of optical fingerprint for personal identification [2]. Their proposal was based on clinical results that every iris is unique and it remains unchanged in clinical photographs. The human iris begins to form during the third month of gestation. The structure is complete by the eighth month of gestation, but pigmentation continues into the first year after birth. It has been discovered that every iris is unique and no two people even two identical twins have uncorrelated iris patterns [3], and is stable throughout the human life. It is suggested in recent years that the human irises might be as distinct as fingerprint for different individuals, leading to the idea that iris patterns may contain unique identification features.

In 1936, Frank Burch, an ophthalmologist, proposed the idea of using iris patterns for personal identification [4]. However, this was only documented by James Doggarts in 1949. The idea of iris identification for automated recognition was finally patented by Aran Safir and Leonard Flom in 1987 [4]. Although they had patented the idea, the two ophthalmologists were unsure as to a practical implementation for the system. They commissioned John Daugman to develop the fundamental algorithms in 1989. These algorithms were patented by Daugman in 1994 and now form the basis for all current commercial iris recognition systems. The Daugman algorithms are owned by Iridian Technologies and they are licensed to several other companies [4].

Many researchers have worked on iris recognition and human iris identification process is basically divided into four steps,

- Localization - the inner and the outer boundaries of the iris are calculated.
- Normalization - Iris of different people may be captured with different sizes, for the same person also the size may vary because of the variation in illumination and other factors.
- Feature extraction - Iris provides abundant texture information. A feature vector is formed which consists of the ordered sequence of features extracted from the various representation of the iris images.
- Matching - The feature vectors are classified through different techniques like Hamming Distance, weight vector and winner selection, dissimilarity function, etc.

The speed and performance of an iris recognition system is crucial and it is usually affected by the outcome of iris localization to a great extent. Iris localization includes finding the iris boundaries (inner and outer) and the eyelids (lower and upper).

The Daugman algorithm [5] locates the pupillary and limbic boundaries of the iris using an integro-differential operator that finds the circles in the image where the intensity changes most rapidly with respect to changes in the radius. Once located, the iris image is converted from a Cartesian form by projecting it onto a dimensionless pseudo-polar coordinate system. Like Daugman, Wildes[6] also used the first derivative of image intensity to find the location of edges which correspond to the borders of the iris. The Wildes algorithm locates the iris boundaries by creating a binary edge map using gradient-based edge detection, and then by finding the centers and radii of these circles via a Hough Transform. The Wildes system explicitly models the upper and lower eyelids with parabolic arcs whereas Daugman excludes the upper and the lower portions of the image. There are some other researchers who have used different algorithms for iris localisation. To locate the iris, Tisse *et al*. [7] apply a gradient decomposed Hough Transform to compute the approximate center of the pupil before applying an integro-differential operator, as in Daugman's algorithm, to compute and extarct the precise locations of the iris boundaries. Boles and Boashash [8] have proposed an algorithm that locates the pupil center using an edge detection method, records grey level values on virtual concentric circles, and then constructs the zero-crossing representation on these virtual circles.

To the best knowledge of the authors, there exist no previous work on iris segmentation and localisation using a multiscale approach. In this paper we propose a novel approach for iris segmentation with multiscale edge detection based on wavelet maxima which can provide significant edges where noise disappears with an increase of the scales (to a certain level), with less texture points producing local maxima thus enabling us to find the real geometrical edges of the image thereby yielding an efficient detection of the significant circles for inner and outer iris boundaries and eyelids. First we detect a multiscale edge map using the information extracted from the wavelet coefficients as demonstrated in [9] thus allowing us to

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obtain finer edges for pupil and iris circles. A Hough transform is used to localise the iris and the pupil. The eyelids are isolated using the horizontal multiscale edge with a linear Hough transform while the eyelashes are isolated using a threshold technique. Finally, the iris image is transformed from Cartesian system of coordinates to polar system of coordinates; this normalisation process being invariant for iris orientation, pupil position in the iris so that the representation is similar to all iris images, with similar dimensions.
The experiments and results obtained have shown that the proposed approach for iris segmentation is effective and robust in the noise.

The rest of the paper is organised as follows: Section 2 describes iris composition and the principle of iris segmentation. Section 3 describes the proposed method including the principles of multiscale edge detection using the wavelet transform. Section 4 is concerned with the results and their analysis and while section 5 concludes the paper.

2. IRIS & ITS SEGMENTATION

2.1 Background

The eye is essentially made up of two parts: the scalera or “white” portion of the eye and cornea. The scalera consists of closely interwoven fibers and a small section in the front and center known as the cornea. The cornea consists of fibers arranged in regular fashion. Conveniently this makes the cornea transparent, allowing light to filter in. Behind the cornea is the anterior chamber filled with a fluid known as the aqueous humor. A spongy tissue, the ciliary bodies, arranged around the edge of the cornea, constantly produces the aqueous humor. Immersed in the aqueous humor is a ring of muscles commonly referred to as iris. The word iris is most likely derived from the Latin word for rainbow. It appears that the term was first applied in the sixteenth century, making reference to this multicoloured portion of the eye [1][6]. The iris itself extends out in front of the lens, forming a circular array, with a variable opening in the center, otherwise known as the pupil . The pupil is not located exactly in the center of the iris, but rather slightly nasally and inferiorly (below the center) [2]. The iris, which is made up of two bands of muscles, controls the pupil, the dilator, which contracts to enlarge the pupil, and the sphincter, which contracts to reduce the size of the pupil. The visual appearance of the iris is directly related to its multi-layered construction.

2.2 Iris Segmentation

Image acquisition will capture the iris as part of a larger image that also contains data derived from the immediately surrounding eye region. Therefore, prior to performing iris pattern matching, it is important to localize that portion of the acquired image that corresponds to an iris [6]. That portion of the image derived from inside the limbus (the border between the sclera and the iris) and outside the pupil (see Figure 1 from CASIA iris database), if the eyelids are occluding part of the iris, then only that portion of the image below the upper eyelid and above the lower eyelid should be included. The eyelid boundary also can be irregular due to the presence of eyelashes. From these suggestions, it can be said that in iris segmentation a wide range of edge contrasts must be taken in consideration, and iris segmentation must be robust and effective.

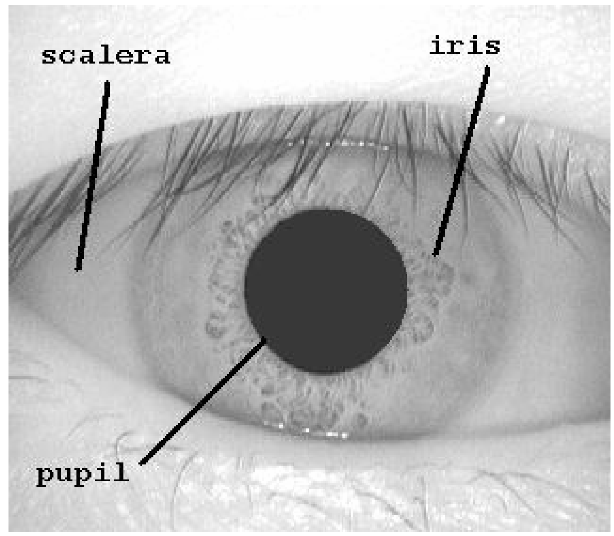

Figure 1.Eye image

3. PROPOSED METHOD FOR IRIS SEGMENTATION

In our proposed method, a multistage edge detection is used to extract the points of sharp variations (edges) with modulus maxima and where the local maxima are detected to produce only single pixel edges. Depending on the requirement of details desired in the edges the level of decomposition can be selected.

3.1 Motivation

3.1.1 Edge detector using wavelets

Edges in images can be mathematically defined as local singularities. Until recently, the Fourier transforms was the main mathematical tool for analyzing singularities. However, the Fourier transform is global and as such not well adapted to local singularities. It is hard to find the location and spatial distribution of singularities with Fourier transforms. On the other hand, Wavelet trasnfroms provide a local analysis; they are especially suitable for time-frequency analysis [12] such as for singularity detection problems. With the growth of wavelet theory, the wavelet transforms have been found to be remarkable mathematical tools to analyze the singularities including the edges, and further,to detect them effectively. Mallat, Hwang, and Zhong [9, 11] proved that the maxima of

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the wavelet transform modulus can detect the location of the irregular structures. The wavelet transform characterizes the local regularity of signals by decomposing signals into elementary building blocks that are well localized both in space and frequency.This not only explains the underlying mechanism of classical edge detectors, but also indicates a way of constructing optimal edge detectors under specific working conditions.

A remarkable property of the wavelet transform is its ability to characterize the local regularity of functions. For an image f(x, y), its edges correspond to singularities of f(x, y), and thus are related to the local maxima of the wavelet transform modulus. Therefore, the wavelet transform can be used as an effective method for edge detection.

Assume f(x, y) is a given image of size $M \times N$. At each scale j with j>0 and $S_0 f = f(x, y)$, the wavelet transform decomposes $S_{j-1} f$ into three wavelet bands : a lowpass band $S_j f$, a horizontal highpass band $W_j^H f$ and a vertical highpass band $W_j^V f$. The three wavelet bands ($S_j f$, $W_j^H f$, $W_j^V f$) at scale j are of size $M \times N$, which is the same as the original image, and all filters used at scale j (j>0) are upsampled by a factor of 2^j compared with those at scale zero.

In addition, the smoothing function used in the construction of a wavelet reduces the effect of noise. Thus, the smoothing step and edge detection step are combined together to achieve the optimal result.

3.1.2 Multiscale edge detection

The resolution of an image is directly related to the appropriate scale for edge detection. High resolution and a small scale will result in noisy and discontinuous edges; low resolution and a large scale will result in undetected edges. The scale controls the significance of edges to be shown. Edges of higher significance are more likely to be preserved by the wavelet transform across the scales. Edges of lower significance are more likely to disappear when the scale increases.

Since an edge separates two different regions, an edge point is a point where the local intensity of the image varies rapidly - more rapidly than in the neighbouring points which are close from the edge: such a point could therefore be characterized as a local maximum of the gradient of the image intensity, The problem is that such a characterization is to be applied to differentiable images, and above all that it also detects all noise points. All techniques used so far to resolve the problem are based on smoothing the image first [5][6][13][14]. However, a problem with smoothing arises: how much and what smoothing should one chooses? A strong smoothing will lead to the detection of less points while a lighter one will be more permissive. That is why Mallat defined, in his work with Zhong [4], the concept of multiscales contours. In this case every edge point of an image is characterized by a whole chain of the scale-space plane: the longer the chains are, the more important is the smoothing we impose, and the smaller the number of edge points we will get. In addition, this allows us to extract useful information about the regularity of the image at the edge point it characterizes. This can be very attractive in terms of a finer characterisation of edge map.

The method of multiscale edge detection described in [10] is used to find the edges. This wavelet is nonsubsampled wavelet decomposition essentially implements the discretized gradient of the image at different scales. At each level of wavelet transform the modulus $M_j f$ of the gradients can be computed by:

$$M_j f = \sqrt{\left|W_j^H f\right|^2 + \left|W_j^V f\right|^2} \tag{1}$$

And the associated phase $A_j f$ is obtained by:

$$A_j f = \tan^{-1}\left(\frac{W_j^V}{W_j^H}\right) \tag{2}$$

The sharp variation points of the image f(x, y) smoothed by $S_j f$ ($f(x, y) * S_j f$) are the points (x, y), where the modulus $M_j f$ has a local maxima in the direction of the gradient given by $A_j f$.

3.2 Proposed Method

Figure 2.Diagram of the proposed method

The multilevel wavelet decomposition is performed and the edge detection is applied and then local maxima is computed to produce both iris outer boundary and pupil boundary edge maps. A Hough transform technique is then performed for the detection of circles (outer and pupil boundaries) followed by a conversion of iris images from cartesian to polar coordinates system as part of a normalisation process. The diagram of this method is illustrated in (figure 2).

3.2.1 Edge map detection

In our work, we have used the algorithm described in [9] to obtain the wavelet decomposition using a pair of discrete filters H, G as shown in Table1.

H	*G*
0	0
0	0
0.125	0
0.375	-2.0
0.375	2.0
0.125	0
0	0

Table 1: Response of filters H, G

At each scale s, the algorithm decomposes the eye image I(x,y) into I(x, y, s) , W_v (x y, s) and W_h (x, y, s)

- I(x, y, s) : the image smoothed at scale s.
- W_h (x, y, s) and W_v (x, y, s) can be viewed as the two components of the gradient vector of the analyzed image I(x,y) in horizantal and vertical direction respectively.

In each scale s (s < S) where S is the number of scales or decomposition., the image I(x, y) is smoothed by a lowpass filter: s=0 ,

$$I(x, y, s+1) = I(x, y, s) * (H_s , H_s) \qquad (3)$$

And horizantal and vertical details are obtained respectively by:

$$W_h (x, y, s) = \frac{1}{\lambda_s} . I(x, y, s) * (G_s , D) \qquad (4)$$

$$W_v (x\, y, s) = \frac{1}{\lambda_s} . I(x, y, s) * (D, G_s) \qquad (5)$$

- We denote by D the Dirac filter whose impulse response is equal to 1 at 0 and 0 otherwise.

- We denote by A * (H, L) the separable convolution of the rows and columns, respectively, of the image A with the 1-d filters H and L.

- G_s, H_s are the discrete filters obtained by putting 2^s-1 zeros between consecutive coefficients of H and G.

- λ_s , as explained in [9] due to discretization, the wavelet modulus maxima of a step edge do not have the same amplitude at all scales as they should in a continuous model. The constants λ_s compensate for this discrete effect. The values of λ_s are given in Table 2.

s	λ_s
1	1.50
2	1.12
3	1.03
4	1.01
5	1.00

Table 2: Normalization coefficient λ_s .for s >5, λ_s =1.

(Figure 3) clearly shows the application of the algorithm on an eye image where it can be observed that the edges of the image in both horizontal and vertical directions and at different scales are efficiently computed.

From (Figure 3) it can be observed that there is significant information about edge information in an eye image, with W_h (x, y, s) eyelids and that the horizontal pupil's lines are clearer than outer boundary circle, and with W_v (x, y, s)

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useful information about both pupil and outer boundary circles.

Figure 3. Original image at the top, the first column on the left shows W_h (x, y, s) for $1 \le s \le 3$, and the second column on the right shows W_v (x, y, s) for $1 \le s \le 3$.

After computing the two components of the wavelet transform, we compute the modulus at each scale as:

$$M(x, y, s) = \sqrt{\left|w_h(x,y,s)\right|^2 + \left|w_v(x,y,s)\right|^2} \qquad (6)$$

The modulus M(x, y, s) has a local maxima in the direction of the gradient given by:

$$A(x, y, s) = \arctan\left(w_v(x,y,s) \big/ w_h(x,y,s) \right) \qquad (7)$$

Figure 4. The first column on the left shows the modulus images M(x, y, s) for $1 \le s \le 5$, and the second column on the right displays intensities along specified column.

A thresholding operation is then applied to the modulus M(x,y, s). This is carried out on the modulus maxima MAX(M(x, y, s)) and then multiplied by a factor α to obtain a threshold value that yields an edge map. The threshold value T is computed as follows:

$$T = \alpha * \mathrm{MAX}\,(M(x, y, s)). \qquad (8)$$

Therefore all values of M(x, y, s) greater or equal to T are considered edge points.
α takes different values for pupil edge detection and outer boundary edge detection.

Figure 5: pupil edge detection in scale s=3 with α =0.66

Figure 6: Outer boundary edge detection using only the vertical coefficients W_v.

The use of vertical coefficients for outer boundary edge detection will reduce the influence of the eyelids when performing a circular Hough transform because the eyelids are usually horizontally aligned [6].

3.2.2 Iris outer and pupil circles detection

The Hough transform locates contours in an n-dimensional parameter space by examining whether they lie on curves of specified shape. For the iris outer or pupillary boundaries and a set of recovered edge points (x_i, y_i), i=1,…,n, a Hough transform is defined as:

$$H(x_c, y_c, r) = \sum_{i=1}^{n} h(x_i, y_i, x_c, y_c, r) \qquad (9)$$

where $H(x_c, y_c, r)$ shows a circle through a point, the coordinates x_c, y_c, r define a circle by the following equation:

$$x_c^2 + y_c^2 + r^2 = 0 \qquad (9.1)$$

In the case of edge detection for iris boundaries the above equation will become:

$$(x_i - x_c)^2 + (y_i - y_c)^2 - r^2 = 0 \qquad (9.2)$$

(a) **(b)**

Figure 7: Iris localized: (a) pupil detected, (b) outer circle detected.

3.2.3 Eyelids and eyelashes isolating

Horizontal coefficients W_h (x,,y,s) are only used for multiscale edge detection to create an edge map as shown in (Figure 8). The eyelids were then isolated by first fitting a line to the upper and lower eyelid parts using a linear Hough transform. A second horizontal line is then drawn, which intersects with the first line at the iris edge that is closest to the pupil; the second horizontal line allows maximum isolation of eyelid regions while the thresholding operation is used to isolate eyelashes (see Figure 9)

Figure 8: Edges for eyelids detection: the first column on the left shows the original images and the second column on the right shows the edges detected using the horizontal coefficients W_h (x, y, 3).

Figure 9: Iris localization without noise.

3.2.4 Iris normalization and polar transformation

Once the iris region is segmented, the next stage is to normalize this part, to enable generation of the iriscode and their comparisons. Since variations in the eye, like optical size of the iris, position of pupil in the iris, and the iris orientation change from person to person, it is required to normalize the iris image, so that the representation is common to all, with similar dimensions.

The normalization process involves unwrapping the iris and converting it into its polar equivalent. It is done using Daugman's Rubber sheet model (see Figure 10). The center of the pupil is considered as the reference point and a remapping formula is used to convert the points on the Cartesian scale to the polar scale.

The remapping of iris image I(x, y) from raw Cartesian coordinates to polar coordinates (r, θ) can be represented as:

$$I(x(r,\theta), y(r,\theta)) \longrightarrow I(r,\theta) \qquad (10)$$

where r is on the interval [0,1] and θ is angle [0,2π],
With:

$$x(r,\theta) = (1-r)x_p(\theta) + r x_l(\theta) \qquad (10.1)$$

$$y(r,\theta) = (1-r)y_p(\theta) + r y_l(\theta) \qquad (10.2)$$

where $x_p(\theta)$, $y_p(\theta)$ and $x_l(\theta)$, $y_l(\theta)$ are the coordinates of the pupil and iris boundaries along the direction θ.

Figure 10. Unwrapping the iris

In this model a number of data points are selected along each radial line and this is defined as the radial resolution. The number of radial lines going around the iris region is defined as the angular resolution as in (see Figure 11).

Figure 11. Draw of the normalised portion with radial resolution of 15 pixels, and angular resolution of 60 pixels.

Figure 12. Normalized iris image

4. RESULTS & ANALYSIS

The proposed algorithm have been tested using the CASIA iris image database, which consists of 80 persons, 108 set eye images and 756 eye images.

Figure 13. Illustration of perfect iris segmentation

A perfect segmentation was obtained as shown in (Figure 13) and a success rate of 99.6% which is the best compared with the basis for all current iris recognition systems (Daugman and Wildes methods).

A multiscale approach can provide a complete and a stable description of signals since it is based on a wavelet formalization of multiscale approach. This characterization provides a new approach to classical iris edge detection problems since all existing research in iris localization is based either on the integro-differential method proposed by Daugman or the derivatives of the images proposed by Wildes. For example, a problem with Daugman's algorithm [5] is that it can fail in the presence of noise (i.e.., from reflections, .. etc) since the algorithm works only on a local scale basis.

However, in the proposed algorithm a multiscale approach provides more useful information about the sharp variations (images at each scale with a horizontal and a vertical decomposition, as shown in Figure2 and demonstrated in [9][10] the scale defines the size of the neighbourhood where the signal changes are computed.

It is clear from (Figure 14) that the proposed algorithm is capable to detect pupil and outer boundary circles even with poor quality iris images because of the efficient edge map detected with multiscale edge detection .

Figure 14. Poor quality iris image is efficiently localized.

On the other hand, there are problems with threshold values to be chosen for edge detection. First this may result in critical edge points being removed, resulting in a failure to detect circles/arcs. Secondly, there is no precise criterion to choose a threshold value. Wildes [6] chose a hard threshold value and applied the Hough transform, but the choice of threshold was not based on solid grounds.

In the proposed algorithm the threshold value is selected by computing the maximum of the modulus at a given scale s which provides a solid criterion, because the sharp variation points of the image smoothed by h(x, y, s) are the pixels at locations (x, y), where the modulus M(x, y, s) has a local maxima in the direction of the gradient A(x, y, s) [10]. It can be clearly seen from (Figure 15) that edges are well detected and the pupil is clearer as shown in (b) and (c) than the edge and pupil as shown in (a). It can also be seen that, as a result, the pupil's circle is well localized as shown in (e). This is the reason why the proposed algorithm outperforms other algorithms which used a local scale and Canny edge detector.

(a) (b) (c)

(d) (e)

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Figure 15. Edge influence in iris segmentation: (a) pupil edge map using Canny edge detector and threshold value (T1= 0.25 and T2=0.25), (b) and (c) pupil edge obtained with a multiscale edge detection using wavelet maxima for $\alpha = 0.4$ and $\alpha = 0.6$ respectively, (d) result of iris segmentation using Canny edge detector of example (a), (e) result of iris segmentation using multiscale edge detection of example (c).

This analysis confirms and explains the effectiveness of our proposed method based on multiscale edge detection using wavelet maxima for iris segmentation provides a precise detection of circles (iris outer boundary and pupil boundary) and a precise edge map obtained from the wavelet decomposition in the horizontal and vertical directions.

This is turn greatly reduces the search space for the Hough transform and performs well in the presence of noise, thereby improving the overall performance with a better success rate than that of Daugman and Wildes methods (see Figure 16).

Figure 16. Success rate of iris segmentation.

5. CONCLUSION & FUTURE WORK

Iris recognition, as a biometric technology, has great potential for security and verification applications. This is mainly due to its variability and stability features. In this paper, a new method for iris segmentation is proposed. The technqiue is based on a multiscale edge detection approach using wavelet maxima as a preprocessing step that is very suitable for the detection of iris outer and inner circles. This approach yields a good localization a necessary step to achieve higher recognition accuracy. Extensive experimentation and its analysis have shown that the proposed method outperforms existing and similar technqiyes with an accuracy of 99.6%.

Further development of this method are under way and the results will be reported in appropriate journals and conferences in due course. In particular we intend to apply and assess the perfromance of this method on a much larger databse having a larger number of people with variations in illumination and iris image sizes.

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